ELSEVIER
Available online at www.sciencedirect.com
ScienceDirect
Procedia Computer Science 22 (2013) 960 – 967
Procedia Computer Science

17th International Conference in Knowledge Based and Intelligent Information and Engineering Systems - KES2013

Human Activity Monitoring using Fuzzified Neural Networks

Manabu Nii[a,b,*], Yoshihiro Kakiuchi[a], Kazunobu Takahama[a], Kazusuke Maenaka[a,c], Kohei Higuchi[c], Takayuki Yumoto[a]

[a]*Graduate School of Engineering, University of Hyogo, 2167 Shosha, Himeji, Hyogo, Japan*
[b]*WPI Immunology Frontier Research Center, Osaka University, Suita, Osaka, Japan*
[c]*ERATO Maenaka Human-sensing Fusion Project, 2167 Shosha, Himeji, Hyogo, Japan*

Abstract

For monitoring and estimating our daily activity, some kinds of devices are available. One of such kinds of monitoring devices is a MEMS based prototype which is developed by the Maenaka Human Sensing Fusion Project. We have developed a estimation method of human activity from three-axis acceleration data using the above-mentioned prototype. This method can estimate our unit activities, such as (1) walking, (2) running, (3) sitting, (4) lying, and (5) standing. In this paper, we propose a system that can find unusual situation from ECG data. Our proposed system is based on the fuzzified neural networks. The fuzzified neural network is trained by using sensing data with reliability grade. Since the fuzzified neural network learns normal state of the subject person, we can understand the ECG state of the subject when we analyze fuzzy outputs from the trained fuzzified neural network. This paper shows estimation results by using actual monitoring data which contains normal state, and artificial unusual data. From the results for the actual monitoring data, we can see that our proposed system was able to estimate the testing data as normal. From the results of estimating artificial unusual data, our proposed system can find the subject person's unusual situation.

Keywords: Fuzzified neural networks; physical condition monitoring; MEMS; ECG

1. Introduction

For maintaining our health, we need to understand our daily physical condition. In order to manage workers' health such as operators of chemical plants, some kinds of detail physical condition records are useful for understanding the situation of the subject. Although almost all such records are normal condition, we would like to find unusual condition. The point where we should pay attention to is not such normal condition but unusual condition. Here, note that we would like to find not always abnormal condition. We would like to find small signs of the abnormal condition. The fuzzy regression analysis is one of the possibility regression analysis methods. Actual data from monitoring devices are compared with the fuzzy outputs estimated by the fuzzy regression. If the actual data are placed outside the fuzzy outputs, then we consider that such data were obtained in some different

*Corresponding author. Tel.: +81-79-167-4919 ; fax: +81-79-167-4919.
E-mail address: nii@eng.u-hyogo.ac.jp.

doi:10.1016/j.procs.2013.09.180

condition that was not included in the training data. That is, we focus on the relation between actual data and fuzzy outputs for finding the signs of abnormal condition.

To estimate human behavior, we have proposed a two-step abstraction based method. The estimation method has two steps of abstraction; (1) classifying raw data from MEMS sensors into action primitives, and (2) mapping a set of action primitives onto descriptions of behaviors. The abstraction based method has some variations. SVM, fuzzy if-then rules, and three-layer neural network based methods were proposed in [1-5]. In [1-5], we have considered the human behavior estimation for helping to record our activity automatically.

In this paper, we propose a fuzzified neural network based unusual condition detection. A fuzzified neural network is one of tools for realizing fuzzy nonlinear regression analysis. The fuzzified neural network is a standard layered neural network with fuzzy weights and biases. Unusual conditions are detected by using the trained fuzzified neural network. Therefore, we can understand unusual conditions of the subject person.

Some research papers like [6], [7] were reported hardware implementations of SVM. HMM-based methods have been proposed in [8], [9] for the similar purpose. We also aim at implementing our method to a small hardware.

2. Fuzzified neural network based condition monitoring

In order to find unusual situation, a fuzzified neural network is used as a fuzzy regression system. We have proposed a failure detection method for chemical plants in [10]. The fuzzified neural network is trained by using training data that consist of normal situation. The trained fuzzified neural network can output possible ECG output for inputs that will be diagnosed by a user. Each training sample has reliability grade. The reliability grade is assigned by human experts or statistics based assignment system. Assigning reliability grade is very important for training fuzzified neural networks. In the following subsection, first, we show the input output relations of fuzzified neural networks. Next, the cost function and the overview of fuzzy outputs are also shown. Then the reliability assignment system is explained.

2.1. Fuzzified neural networks

For learning the usual state, five samples of ECG ($ECG_{t-5}, \cdots, ECG_{t-1}$) and five samples of three-axis acceleration sensor ($acc^x_{t-5}, \cdots acc^x_{t-1}$, $acc^y_{t-5}, \cdots acc^y_{t-1}$, and, $acc^z_{t-5}, \cdots acc^z_{t-1}$) are used as inputs. The target output is the next one sample of ECG (ECG_t). That is, we estimate the next ECG by using the previous five data from three-axis acceleration and ECG sensors.

Now we define an input vector as follows;

$$\boldsymbol{x}_p = (x_{p1}, \cdots, x_{pn}, y_p; h_p), \quad p = 1, \cdots, N_{\text{samples}} \tag{1}$$

where $x_{pi}, i = 1, \cdots, n$ are real inputs, y_p is the target output, h_p is the reliability grade for the input-output pair, p is the index of a sample, and N_{samples} is the number of samples (i.e., the number of data). When an input vector $\boldsymbol{x}_p$ is input to a fuzzified neural network, the input output relations are described as follows;

$$\text{Input Layer:} \quad o_{pi} = x_{pi}, \quad i = 1, \cdots, n \tag{2}$$

$$\text{Hidden Layer:} \quad O_{pj} = f(Net_{pj}), \quad j = 1, \cdots, n_{\text{H}} \tag{3}$$

$$Net_{pj} = \sum_{i=1}^{n} o_{pi} \cdot W_{ji} + \Theta_j, \tag{4}$$

$$\text{Output Layer:} \quad O_p = f(Net_p), \tag{5}$$

$$Net_p = \sum_{j=1}^{n_{\text{H}}} O_{pj} \cdot W_j + \Theta, \tag{6}$$

where O_{pj} and O_p are fuzzy outputs, W_{ji} and W_j are fuzzy weights, Θ_j and Θ are fuzzy biases, and $f(\cdot)$ is sigmoidal activation function. In our research, fuzzy weights and biases have asymmetric trapezoidal fuzzy membership functions. Figure 1 shows an asymmetric trapezoidal fuzzy membership function. Since such asymmetric

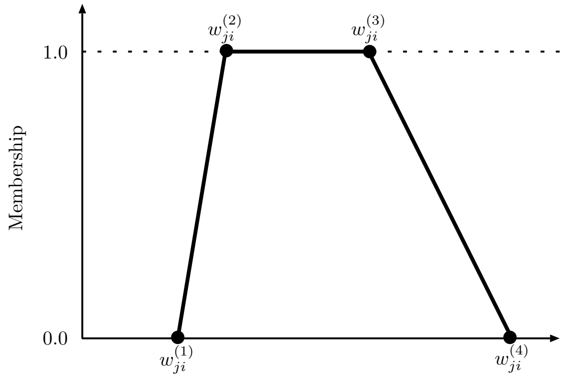

Fig. 1. Asymmetric trapezoidal fuzzy membership function

trapezoidal fuzzy numbers are used for weights and biases, the outputs of the fuzzified neural network have trapezoidal like shape.

For training the fuzzified neural network, a cost function is defined as the following manner.

1. if $[O_p]^L_{h_p} < y_p < [O_p]^U_{h_p}$, then

$$e_p = \epsilon \cdot (y_p - [O_p]^L_{h_p})^2/2 + \epsilon \cdot (y_p - [O_p]^U_{h_p})^2/2, \tag{7}$$

2. if $y_p < [O_p]^L_{h_p} < [O_p]^U_{h_p}$, then

$$e_p = (y_p - [O_p]^L_{h_p})^2/2 + \epsilon \cdot (y_p - [O_p]^U_{h_p})^2/2, \tag{8}$$

3. if $[O_p]^L_{h_p} < [O_p]^U_{h_p} < y_p$, then

$$e_p = \epsilon \cdot (y_p - [O_p]^L_{h_p})^2/2 + (y_p - [O_p]^U_{h_p})^2/2, \tag{9}$$

where ϵ is a small constant (e.g., $\epsilon = 0.01$). Therefore, the fuzzified neural network is trained as the fuzzy output includes the target signal by the backpropagation based algorithm. Figure 2 shows an example of fuzzy outputs for the ECG data. Red line is the actual ECG data used as the training data. Green, blue, and purple lines are 0.0, 1.0, and *Reliability* level sets of the fuzzy outputs, respectively. In this example, $h_p = 0.6$ is assigned for every training input-output pair. The 0.6-level set (i.e., purple lines) of the fuzzy output includes actual ECG data. When we desire that each training input-output pair is included by 0.5-level set of the fuzzy output of the trained fuzzified neural network, we will assign $h_p = 0.5$ to every training input-output pair. We can assign different h_p to each input-output pair.

2.2. *Finding unusual situation from fuzzy outputs*

When the training data consist of usual condition of the subject person, we can consider that the trained fuzzified neural network learned normal situation of the subject person. Therefore, when the fuzzy output from the trained fuzzified neural network includes the actual output, we can consider the state of the subject is normal. On the other hand, the state of the subject is unusual when the actual output is outside of the fuzzy output (i.e., the actual output is placed outside of 0.0-level set of fuzzy output). Moreover, when the above mentioned unusual situation is caused in a certain period, we can consider that the subject's state is unusual. Taken together, when the actual outputs are included by lower level set of fuzzy outputs in a certain period, or when the actual outputs are placed outside of 0.0-level set of fuzzy outputs, we decide the subject is unusual.

We define a evaluation value EV_t to measure the degree of unusual condition. We define the following rules for finding unusual state of the subject person.

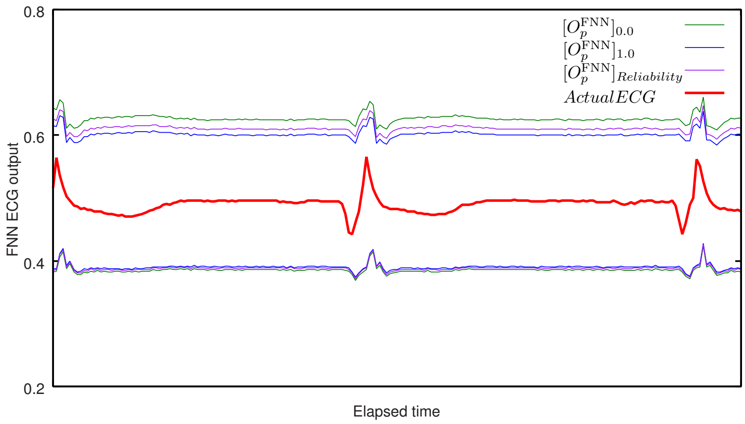

Fig. 2. An example fuzzy output from trained fuzzified neural networks

1. If the actual outputs y_p are placed outside of 0.0-level set of fuzzy outputs, then EV_t is assigned the predefined largest value.
2. If the actual outputs y_p are placed in from 0.0-level to h_p-level set of fuzzy outputs, then EV_t is assigned a certain value according to the predefined EV table.
3. If the actual outputs y_p are included in above h_p-level set of fuzzy outputs, then $EV_t = 0.0$. This is because the y_p is in usual condition of the subject person.

Where t is the index of the considering period. Hence, the total evaluation value TEV is defined as follows;

$$TEV = \sum_{t=1}^{T} EV_t, \tag{10}$$

where T is the predefined considering period.

3. Experimental results

3.1. Datasets

In order to prepare datasets, a MEMS based monitoring device was used for monitoring human physical condition. The MEMS based monitoring device used in this paper was proposed in [11-14] to monitor our daily physical condition. They aimed at developing a ultra-small monitoring device that consists of MEMS based sensors for realizing noninvasive and unconstrained monitoring. We used a prototype of such monitoring device for obtaining data of our physical condition. The device has three-axis acceleration, pressure, and ECG sensors. The device can record all kinds of data simultaneously. The acceleration sensor and ECG data are obtained with the sampling rate of 125 Hz. The obtained raw data were used as training data for fuzzified neural networks. Testing data were obtained with the same manner on the same subject person.

3.2. Results of fuzzified neural network based unusuall condition detection

In this subsection, results of the unusual condition detection are shown. For training fuzzified neural networks, acceleration and ECG sensor data were used as;

$$\boldsymbol{x}_t = (ECG_{t-5}, \cdots, ECG_{t-1}, acc^x_{t-5}, \cdots acc^x_{t-1}, acc^y_{t-5}, \cdots acc^y_{t-1}, acc^z_{t-5}, \cdots acc^z_{t-1}, ECG_t; h_t), \tag{11}$$

where t is the index of a sample point. Five sample points were used for inputs. That is, five acceleration sensor data for each axis and five values of ECG at the corresponding sample points were input to a fuzzified neural

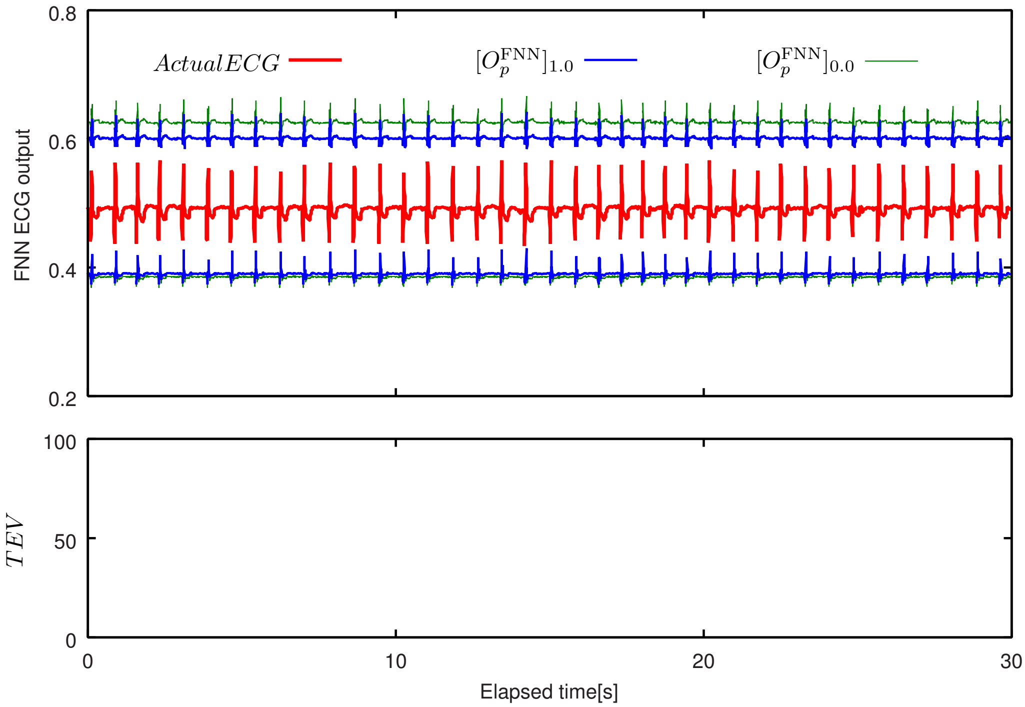

Fig. 3. Fuzzy output for the training data

network. The target value for each input vector is a value of ECG at the next sample point. The reliability grade for each input-output pair is assigned to $h_t = 0.6$.

Figure 3 shows fuzzy output from the trained fuzzified neural network. A red line depicts the actual ECG data. The blue and green lines are 1.0-level set and 0.0-level set of fuzzy output, respectively. We can see from Fig.3 the actual ECG data used for training were included by the fuzzy output from the trained fuzzified neural network. Especially, the actual ECG was included by the 1.0-level set of the fuzzy output. Since all actual ECG data were included by the 1.0-level set of the fuzzy output, TEV shows $TEV = 0.0$ (see, the lower graph in Fig.3). Therefore, we can conclude that the subject person was in usual condition in this case. This is a natural result because the actual ECG data shown in this figure were used as the training data.

Figure 4 shows another result. In Fig.4, although the red line means the actual ECG data on the same subject, they were not used for training. The red line protrudes from the 1.0-level set at some points, but it was almost all included by the h_p-level set of the fuzzy output and TEV shows $TEV = 0.0$. Therefore, we can conclude that the subject person was in usual condition in this case. This is a good result because the actual ECG data represent usual condition for the subject while it was not used for training.

On the other hand, when the artificial data, which were generated by changing values of ECG (note that values of acceleration sensor were not changed), were input to the trained fuzzified neural network, the actual ECG data protruded from not only 1.0-level set but also 0.0-level set of the fuzzy output (see, Fig. 5). We can see that TEV has large values all over the elapsed time. Therefore, our proposed finding rules can indicate the unusual condition of the subject person. In Table 1, the predefined evaluation values, which measure the degree of unusual condition, are shown. The consideration period T is set $T = 5$ seconds. Currently, the evaluation values and the consideration period were defined by hand to adapt the subject person.

In Fig.6, the values of ECG were exchanged from the obtained values of *lying* to *running* on about 15 to 30 seconds (see, the upper graph in this figure). That is, the data except ECG are in the *lying* state. This artificial situation represents the subject person has unusual ECG in 15 to 30 seconds when he is lying on some place. Therefore, the unusual condition from 15 to 30 seconds should be founded by our proposed system. We can see

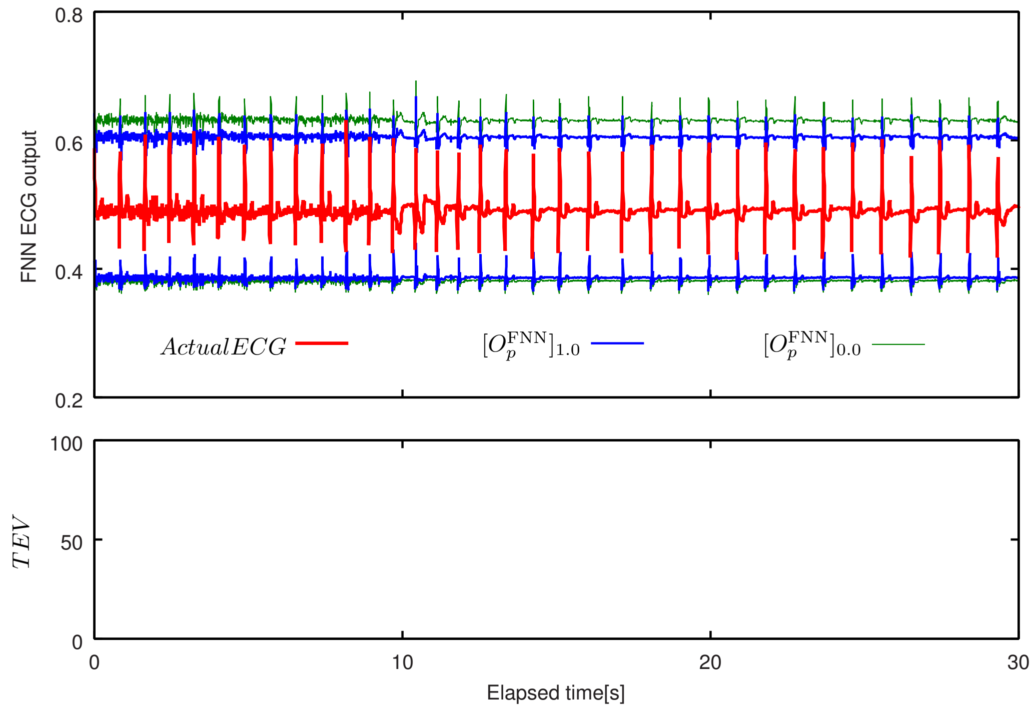

Fig. 4. Fuzzy output for the other normal condition

Table 1. Predefined evaluation values EVs

Relations between a FNN output O_p and an actual output y_p	Predefined values of EV
$[O_p]^L_{1.0} \leq y_p \leq [O_p]^U_{1.0}$	0
$[O_p]^L_{0.8} \leq y_p < [O_p]^L_{1.0}$, or $[O_p]^U_{1.0} < y_p \leq [O_p]^U_{0.8}$	0
$[O_p]^L_{0.6} \leq y_p < [O_p]^L_{0.8}$, or $[O_p]^U_{0.8} < y_p \leq [O_p]^U_{0.6}$	0
$[O_p]^L_{0.4} \leq y_p < [O_p]^L_{0.6}$, or $[O_p]^U_{0.6} < y_p \leq [O_p]^U_{0.4}$	1
$[O_p]^L_{0.2} \leq y_p < [O_p]^L_{0.4}$, or $[O_p]^U_{0.4} < y_p \leq [O_p]^U_{0.2}$	2
$[O_p]^L_{0.0} \leq y_p < [O_p]^L_{0.2}$, or $[O_p]^U_{0.2} < y_p \leq [O_p]^U_{0.0}$	3
$y_p < [O_p]^L_{0.0}$, or $[O_p]^U_{0.0} < y_p$	4

that the TEV was increasing at 15 seconds from the TEV graph in Fig. 6. Since the total of the evaluation values exceeded the predefined threshold and from the results of action estimation, we can conclude that the subject was unusual condition when the subject was lying.

4. Conclusion

In this paper, we proposed a fuzzified neural network based human condition monitoring system. Our proposed system is based on the fuzzy nonlinear regression. Fuzzified neural networks were used to realize fuzzy nonlinear regression models.

Training data consist of normal situation's data of the subject person, because the fuzzified neural network should learn the subject's usual condition. From experimental results, we can see that the fuzzified neural networks can learn the subject's usual condition. In order to find unusual condition of the subject person, we defined an evaluation value EV and its total TEV. Using TEV index, we can find the unusual condition of the subject person.

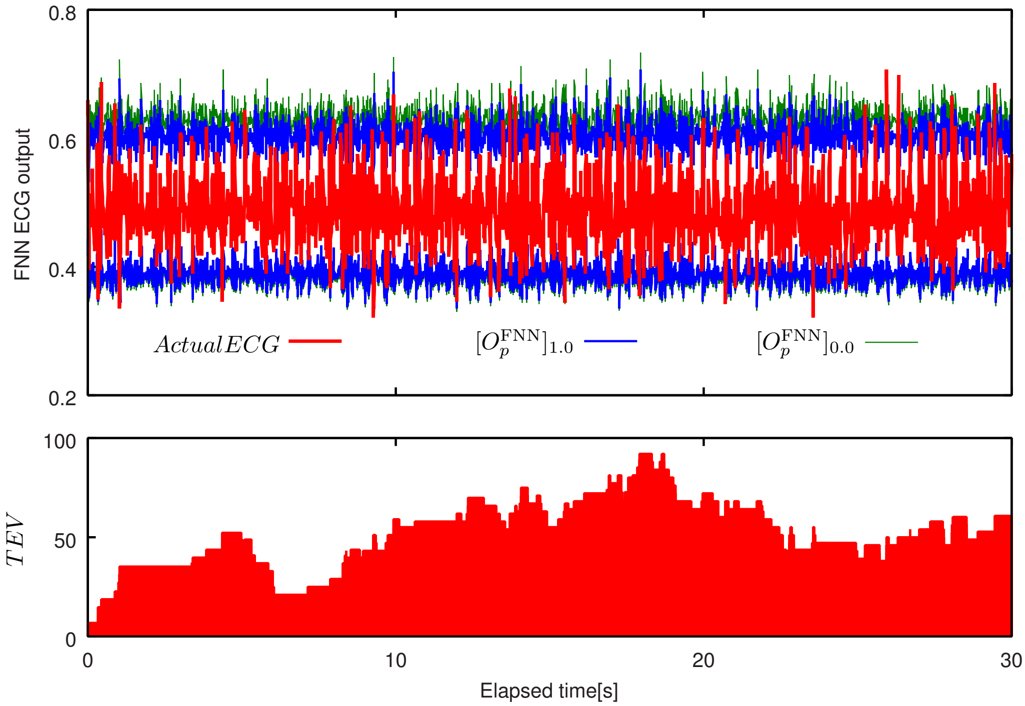

Fig. 5. Fuzzy output for the artificial unusual condition

Our future tasks are more experiments for several kinds of subjects. The dataset used in this paper was obtained from a single subject. To show the effectiveness of our proposed system, we need to more experiments for several kinds of subjects. Accordingly, an automatically setting procedure of some predefined parameters will be needed. Moreover, from the results of the neural network based action estimation [1-5], we can explain what the subject was doing when the condition occurred. This kind of information is helpful for us to understand the situation.

References

[1] M. Nii, K. Nakai, T. Fujita and Y. Takahashi, "Action Estimation from Human Activity Monitoring Data using Soft Computing Approach", Proc. of Third International Conference on Emerging Trends in Engineering and Technology, 2010, pp. 434–439.

[2] M. Nii, K. Nakai, Y. Takahashi, K. Higuchi, and K. Maenaka, "A Human State Estimation Method using Fuzzy based System", Proc. of 2011 Fourth International Conference on Emerging Trends in Engineering & Technology, pp. 151–155.

[3] M. Nii, K. Nakai, Y. Takahashi, K. Higuchi, and K. Maenaka, "Behavior Extraction from Multiple Sensors Information for Human Activity Monitoring", Proc. of 2011 IEEE International Conference on Systems, Man, and Cybernetics, pp. 1157–1161.

[4] M. Nii, K. Nakai, Y. Takahashi, K. Maenaka, and K. Higuchi, "Human Action Classification for a Small Size Physical Condition Monitoring System," Proc. of 2012 World Automation Congress, Puerto Vallarta, Mexico, 2012, WAC 2012 1569535303.

[5] M. Nii, Y. Kakiuchi, T. Tanaka, K. Maenaka, K. Higuchi, "Implementation of a Intelligent System into a Small Physical Condition Monitoring Device for Healthcare," 2012 IEEE International Conference on Systems, Man, and Cybernetics, pp. 2052–2057

[6] F.M. Khan, M.G. Arnold, and W.M. Pottenger, "Hardware-based support vector machine classification in logarithmic number systems", Proc. of IEEE International Symposium on Circuits and Systems, 2005, Vol. 5, pp. 5154–5157.

[7] A. Ghio, S. Pischiutta, "A Support Vector Machine based pedestrian recognition system on resource-limited hardware architectures", Research in Microelectronics and Electronics Conference, 2007, pp. 161–163.

[8] Bok-Gue Park, Koon-shik Cho, and Jun-Dong Cho, "Low power VLSI architecture of Viterbi scorer for HMM-based isolated word recognition", Proc. of International Symposium on Quality Electronic Design, 2002, pp. 235–239.

[9] S.A. Fahmy, P.Y.K. Cheung, and W. Luk,"Hardware acceleration of hidden Markov model decoding for person detection", Proc. of Design, Automation and Test in Europe, 2005, Vol. 3, pp. 8–13.

[10] D. Kimura, M. Nii, T. Yamaguchi, Y. Takahashi, T. Yumoto, "Fuzzy Nonlinear Regression Analysis Using Fuzzified Neural Networks for Fault Diagnosis of Chemical Plants," Journal of Advanced Computational Intelligence and Intelligent Information, Vol.15, No.3, pp. 336–344

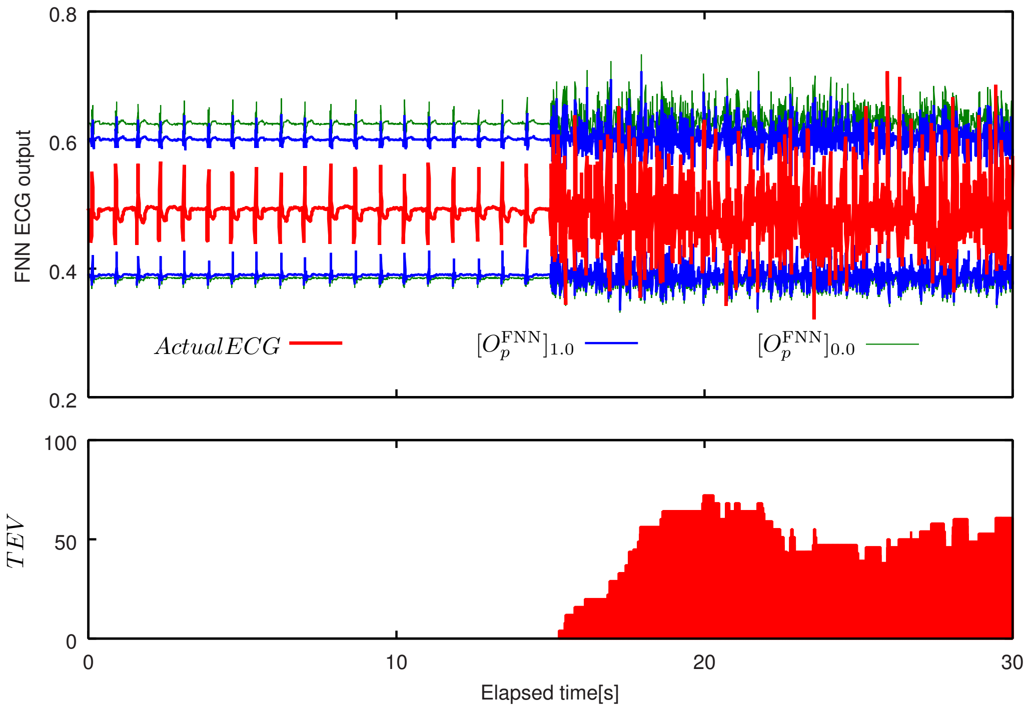

Fig. 6. Result of our proposed detection method

[11] T. Fujita, K. Masaki, and K. Maenaka, "Human Activity Monitoring System Using MEMS Sensors and Machine Learning," Journal of Japan Society for Fuzzy Theory and Intelligent Informatics, 20 (1), 2008, pp. 3–8.

[12] T. Fujita, K. Kanda, K. Maenaka, J. Okada, S. Okochi, and K. Higuchi, "Multi-Environmental Sensing device for Human Monitoring Applications," The 4 th International Symposium on Computational Intelligence and Industrial Applications, Aug. 2010, pp. 65–69.

[13] T. Tanaka, K. Sonoda, S. Okochi, A. Chan, M. Nii, K. Kanda, T. Fujita, K. Higuchi, and K. Maenaka, "Wearable Health Monitoring System and its Applications", Proc. of 2011 Fourth International Conference on Emerging Trends in Engineering & Technology, pp. 143–146.

[14] T. Tanaka, T. Fujita, K. Sonoda, M. Nii, K. Kanda, K. Maenaka, A. C. C. Kit, S. Okochi, K. Higuchi, "Wearable Health Monitoring System by Using Fuzzy Logic Heart-Rate Extraction," Proc. of 2012 World Automation Congress, Puerto Vallarta, Mexico, 2012, WAC-2012-1569536039